Analyzing and Classifying Fast Food Reviews

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Business Case

- Approx. 37% of Americans regularly eat fast food
- Common for customers to post reviews online
- 33% of people read other guests' reviews before selecting place to eat
- Valuable insights can be gained from negative reviews
- Classifying negative reviews can help managers identify pain points efficiently

Data Objectives

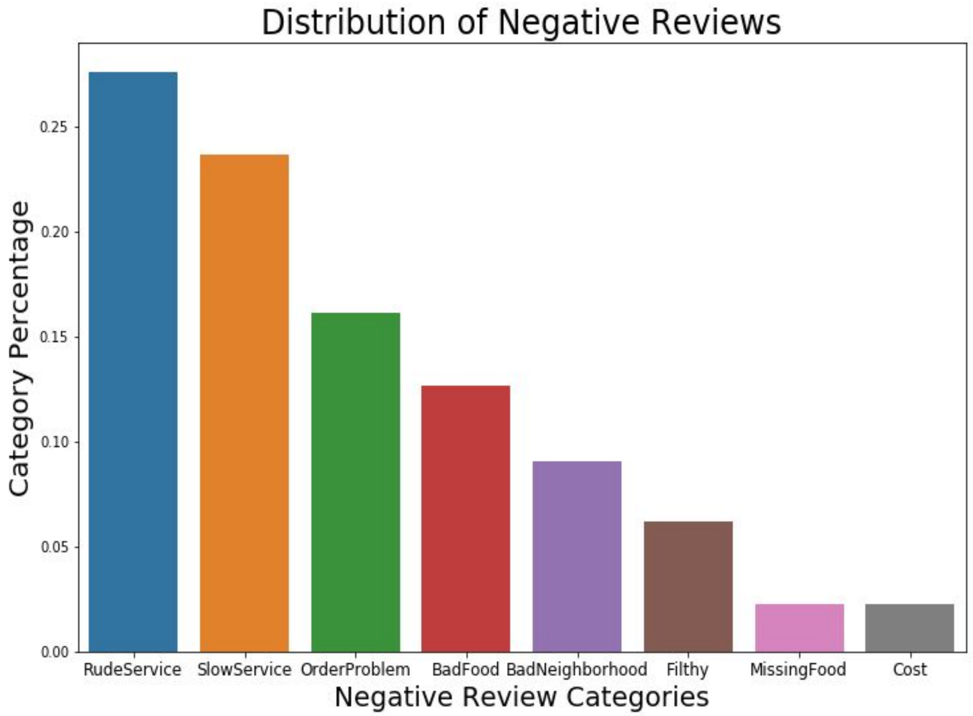
- Negative Yelp reviews for McDonald's restaurants across 9 major U.S. cities
- 8 categories for reviews (e.g. Rude Service, Bad Food, Filthy, etc.)
- Analyze user reviews and class variation between cities
- Develop NLP classification model to classify negative reviews
- Try model on reviews for other fast food restaurants

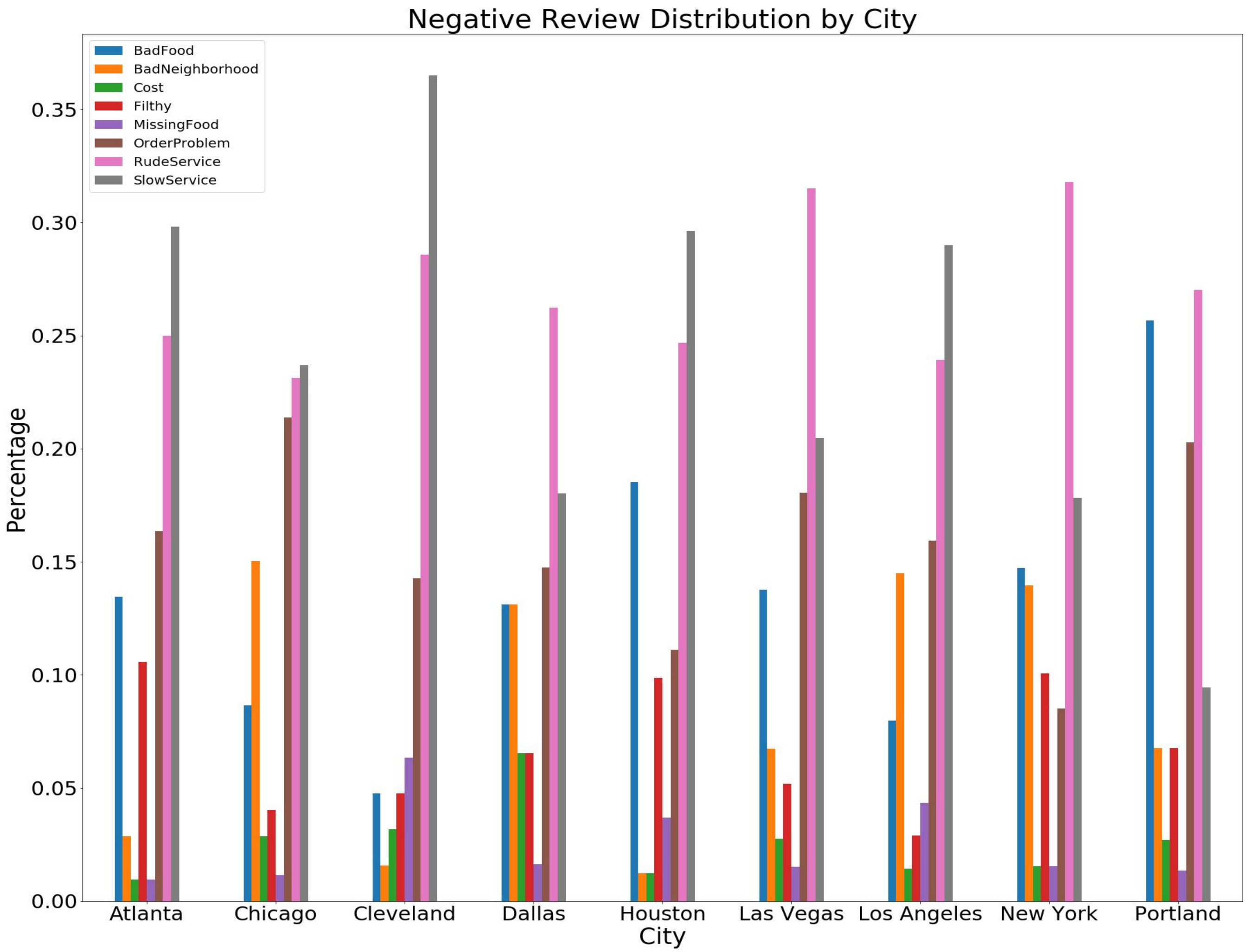
Models

Method	Random Forest	Naive Bayes
Stem -> Lem	Accuracy: 0.592 F1: 0.573	Accuracy: 0.531 F1: 0.517
Lem -> Stem	Accuracy: 0.596 F1: 0.577	Accuracy: 0.531 F1: 0.517
Stem	Accuracy: 0.620 F1: 0.599	Accuracy: 0.523 F1: 0.503
Lem	Accuracy: 0.531 F1: 0.505	Accuracy: 0.510 F1: 0.482
Smote	Accuracy: 0.592 F1: 0.574	Accuracy: 0.522 F1: 0.502
ADASYN	Accuracy: 0.592 F1: 0.575	Accuracy: 0.522 F1: 0.502

Negative Review Categories

- Interactions with restaurant staff are important
- High expectations of quick service (i.e. “Fast Food”)
- Missing Food and Cost complaints more rare

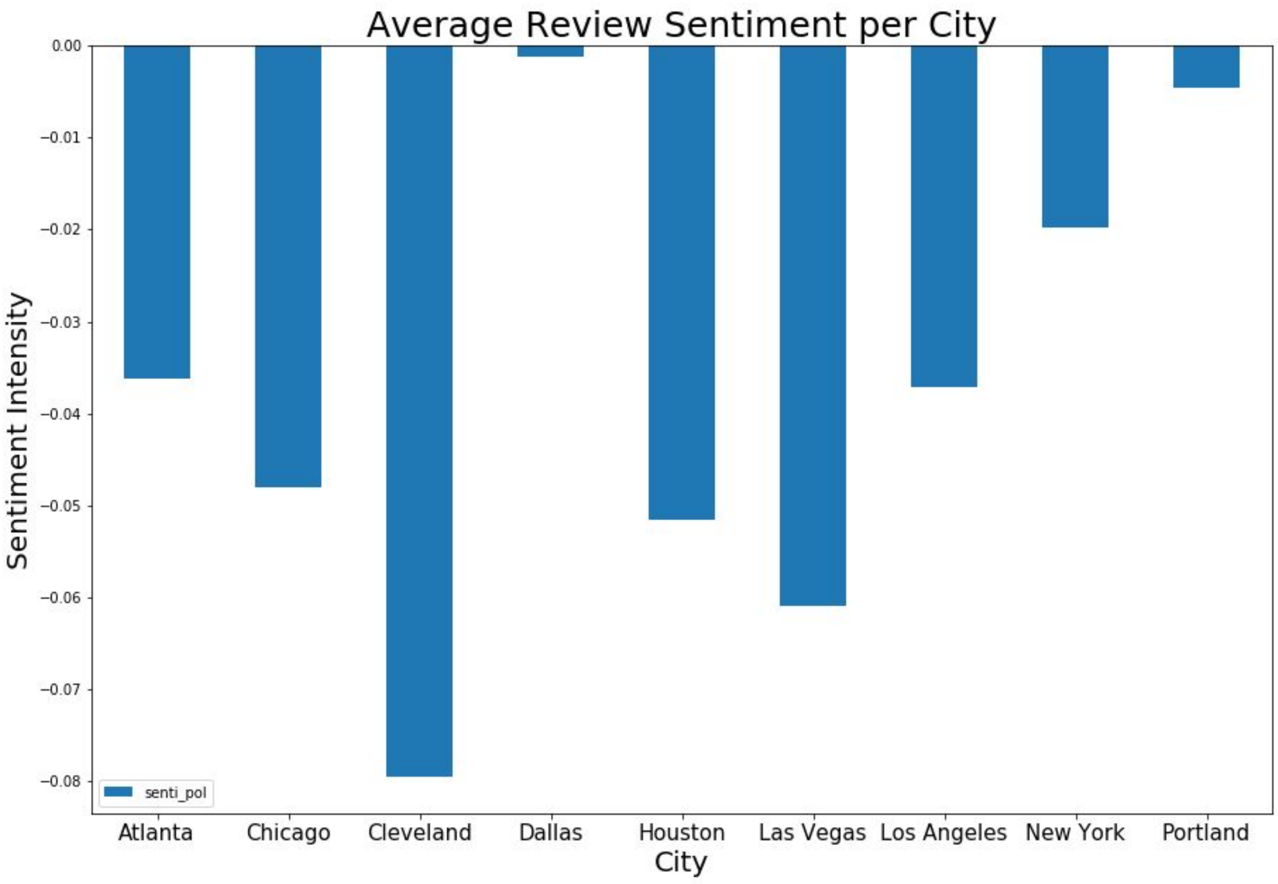




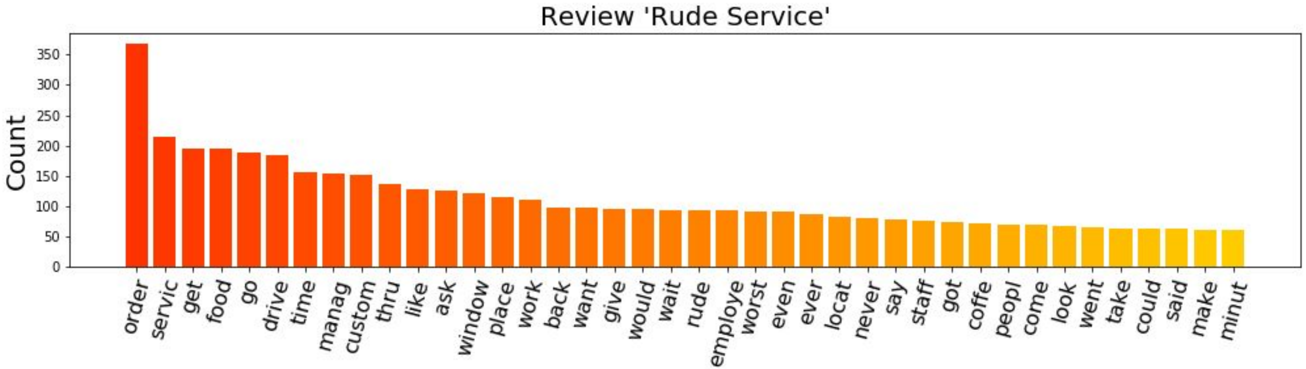
Reviews by City

Sentiment by City

- Sentiment Analyzed using Text Blob
- Cleveland had the most intensely negative reviews on average



Word Frequency for Rude Service and Slow Service



Preprocessing, Feature Engineering and Modeling

- Stemming words worked better than lemmatization
- TF-IDF used to vectorize review words
- Used Random Forest and Naive Bayes classifiers on 4 sets of preprocessed data
- Tried ADASYN and SMOTE to handle class imbalance and improve our model
- Final model parameters:
  - Random Forest
    - Stemmed words
    - n_estimators=250
    - Accuracy score = 0.620
    - F1 score (weighted) =0.599

Classifying KFC Reviews

	text	sentiment
0	I went here tonight to get some food with my friend and from the time I pulled up to order my food and get my food it was already a terrible...	OrderProblem
1	Two lousy buckets of chicken in two months. We used to love KFC but this specific restaurant has killed our taste for KFC. The last 12 piece bucket we...	BadFood
2	On several occasions I've come maybe an hour or so before close (9:45-9:50 and they "supposedly" close at 11 pm) and they're ALWAYS "out" of everything...	RudeService
3	Rude and ghetto , you will be talking to\n2 different ppl at the driver thru every time and will short you on your order.	RudeService
4	Would leave a once star review if i could.\nI ordered the $30 fill up. once I got home (7 miles away), I discovered they had not included the chicken strip...	OrderProblem
5	I ordered online and set it to be delivered. I waited 29 minutes after it was supposed to be delivered before going up to the restaurant and grabbing the...	SlowService
6	I should have read the reviews before walked in the door. Coming from out of state, I thought all KFCs had a standard... boy was I mistaken.\n\nFor starters...	RudeService
7	Was it everyone's first day?! Jesus! And by everyone I mean all 3 employees. Waited 30 minutes for food and it was not even right. These people need to...	SlowService
8	Terrible service. Just took 37 minutes to get our food after all we got was a sorry it'll be 5 more minutes. Manager refused to give money back. Shiniqua...	RudeService
9	Usually the service is pretty good here.\n\nHowever, the last several times I have visited this location, there is either a long wait time, or they get my...	SlowService

1. Can be 'BadFood' or 'OrderProblem', half correct; 2. Correct; 3. Shall be 'OrderProblem'; 4. Correct;
5. Shall be MissingFood; 6. Correct; 7. Cannot determine; 8. Correct;
9. Can be 'RudeService' or 'SlowService', half correct; 10. Correct;

Discussion

Limitations

- Limited data set with high class imbalance and many classes
- Many single review can fall into multiple classes
- User reviews can be hard to interpret or completely irrelevant to the restaurant

Conclusions and Recommendations

- Reviews are critical in the food service industry
- Classifying negative reviews help identify certain problems and help restaurant managers to improve business
- Yelp shall launch this project to categorize the negative reviews and provide results to restaurant owner as a paid service
- Pay attention to staff interactions with customers
- Establish an efficient process to serve guests
- Monitor food preparation and restaurant sanitation

Thank You!